Computer Vision - Lecture 2

Binary Image Analysis

26.10.2015

Bastian Leibe
RWTH Aachen
http://www.vision.rwth-aachen.de/
leibe@vision.rwth-aachen.de
Announcements

• Course webpage
  - http://www.vision.rwth-aachen.de/teaching/
  - Slides will be made available on the webpage

• L2P electronic repository
  - Exercises and supplementary materials will be posted on the L2P

• Please subscribe to the lecture on the Campus system!
  - Important to get email announcements and L2P access!
  - Bachelor students please also subscribe
Binary Images

- Just two pixel values
- Foreground and background
- Regions of interest

<table>
<thead>
<tr>
<th>1</th>
<th>1</th>
<th>0</th>
<th>1</th>
<th>1</th>
<th>1</th>
<th>0</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
Uses: Industrial Inspection

Fig. 3 Schematic diagram of marking inspection setup at Texas Instruments

R. Nagarajan et al. “A real time marking inspection scheme for semiconductor industries“, 2006
Uses: Document Analysis, Text Recognition

Handwritten digits

Natural text (after detection)

Scanned documents

Source: Till Quack, Martin Renold

B. Leibe
Uses: Medical/Bio Data

Source: D. Kim et al., Cytometry 35(1), 1999
Uses: Blob Tracking & Motion Analysis

**Frame Differencing**

![Frame Differencing Example](source: Kristen Grauman)

**Background Subtraction**

![Background Subtraction Example](source: Tobias Jäggli)
Uses: Shape Analysis, Free-Viewpoint Video

Silhouette

Medial axis

Visual Hull Reconstruction

Blue-c project, ETH Zurich
Uses: Intensity Based Detection

- Looking for dark pixels...

\[
\text{fg\_pix} = \text{find}(\text{im} < 65);
\]
Uses: Color Based Detection

• Looking for pixels within a certain color range...

\[ \text{fg\_pix} = \text{find}(\text{hue} > t1 \& \text{hue} < t2); \]
Issues

• How to demarcate multiple regions of interest?
  - Count objects
  - Compute further features per object

• What to do with “noisy” binary outputs?
  - Holes
  - Extra small fragments

Slide Credit: Kristen Grauman
Outline of Today’s Lecture

• Convert the image into binary form
  ➢ Thresholding

• Clean up the thresholded image
  ➢ Morphological operators

• Extract individual objects
  ➢ Connected Components Labeling

• Describe the objects
  ➢ Region properties
Thresholding

- Grayscale image $\Rightarrow$ Binary mask
- Different variants
  - One-sided
    \[ F_T[i, j] = \begin{cases} 
    1, & \text{if } F[i, j] \geq T \\
    0, & \text{otherwise} 
    \end{cases} \]
  - Two-sided
    \[ F_T[i, j] = \begin{cases} 
    1, & \text{if } T_1 \leq F[i, j] \leq T_2 \\
    0, & \text{otherwise} 
    \end{cases} \]
  - Set membership
    \[ F_T[i, j] = \begin{cases} 
    1, & \text{if } F[i, j] \in Z \\
    0, & \text{otherwise} 
    \end{cases} \]
Selecting Thresholds

• Typical scenario
  - Separate an object from a distinct background

• Try to separate the different grayvalue distributions
  - Partition a bimodal histogram
  - Fit a parametric distribution (e.g. Mixture of Gaussians)
  - Dynamic or local thresholds

• In the following, I will present some simple methods.
  - We will then see some more general methods in Lecture 6...
A Nice Case: Bimodal Intensity Histograms

Ideal histogram, light object on dark background

Actual observed histogram with noise

Source: Robyn Owens
Not so Nice Cases...

- How to separate those?

- Threshold selection is difficult in the general case
  - Domain knowledge often helps
  - E.g. Fraction of text on a document page (⇒ histogram quantile)
  - E.g. Size of objects/structure elements

Source: Shapiro & Stockman
Global Binarization [Otsu’79]

- Search for the threshold $T$ that minimizes the within-class variance $\sigma_{within}$ of the two classes separated by $T$

$$\sigma_{within}^2(T) = n_1(T)\sigma_1^2 + n_2(T)\sigma_2^2(T)$$

where

$$n_1(T) = |\{I(x,y) < T\}|,$$ $$n_2(T) = |\{I(x,y) \geq T\}|$$

- This is the same as maximizing the between-class variance $\sigma_{between}$

$$\sigma_{between}^2(T) = \sigma^2 - \sigma_{within}^2(T)$$

$$= n_1(T)n_2(T) \left[ \mu_1(T) - \mu_2(T) \right]^2$$
Algorithm

1. Precompute a cumulative grayvalue histogram $h$.
2. For each potential threshold $T$
   a) Separate the pixels into two clusters according to $T$
   b) Look up $n_1, n_2$ in $h$ and compute both cluster means
   c) Compute $\sigma_{\text{between}}^2(T) = n_1(T)n_2(T)[\mu_1(T) - \mu_2(T)]^2$
3. Choose $T^* = \arg \max_T [\sigma_{\text{between}}^2(T)]$
Local Binarization [Niblack’86]

- Estimate a local threshold within a small neighborhood window $W$

$$T_W = \mu_W + k \cdot \sigma_W$$

where $k \in [-1,0]$ is a user-defined parameter.

Effect:

What is the hidden assumption here?
Effects

Original image

Global threshold selection (Otsu)

Local threshold selection (Niblack)
Additional Improvements

- Document images often contain a smooth gradient

⇒ Try to fit that gradient with a polynomial function

Source: S. Lu & C. Tan, ICDAR’07
Polynomial Surface Fitting

- Polynomial surface of degree \( d \)
  \[
  f(x, y) = \sum_{i+j=0}^{d} b_{i,j} x^i y^j
  \]

- For an image pixel \((x_0, y_0)\) with intensity \(I_0\), this means
  \[
  b_{0,0} + b_{1,0} x_0 + b_{0,1} y_0 + b_{2,0} x_0^2 + b_{1,1} x_0 y_0 + \cdots + b_{0,3} y_0^3 = I_0
  \]

- Least-squares estimation, e.g. for \( d = 3 \)

\[
\begin{bmatrix}
1 & x_0 & y_0 & x_0^2 & x_0 y_0 & \cdots & y_0^3 \\
1 & x_1 & y_1 & x_1^2 & x_1 y_1 & \cdots & y_1^3 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
1 & x_n & y_n & x_n^2 & x_n y_n & \cdots & y_n^3
\end{bmatrix}
\begin{bmatrix}
b_{0,0} \\
b_{1,0} \\
\vdots \\
b_{0,3}
\end{bmatrix}
= 
\begin{bmatrix}
I_0 \\
I_1 \\
\vdots \\
I_n
\end{bmatrix}
\]

Solution with pseudo-inverse:
\[
b = (A^T A)^{-1} A^T I
\]

Matlab (using SVD):
\[
b = I \backslash A
\]
Surface Fitting

• Iterative Algorithm
  1.) Fit parametric surface to all points in region.
  2.) Subtract estimated surface.
  3.) Apply global threshold (e.g. with Otsu method)
  4.) Fit surface to all background pixels in original region.
  5.) Subtract estimated surface.
  6.) Apply global threshold (Otsu)
  7.) Iterate further if needed...

• The first pass also takes foreground pixels into account.
  - This is corrected in the following passes.
  - Basic assumption here: most pixels belong to the background.
Result Comparison

Original image

Global (Otsu)

Local (Niblack)

Polynomial + Global

Source: S. Lu & C. Tan, ICDAR’07
Outline of Today’s Lecture

• Convert the image into binary form
  ➢ Thresholding

• Clean up the thresholded image
  ➢ Morphological operators

• Extract individual objects
  ➢ Connected Components Labeling

• Describe the objects
  ➢ Region properties

Image Source: D. Kim et al., Cytometry 35(1), 1999
Cleaning the Binarized Results

- Results of thresholding often still contain noise

- Necessary cleaning operations
  - Remove isolated points and small structures
  - Fill holes

⇒ Morphological Operators
Morphological Operators

• Basic idea
  - Scan the image with a structuring element
  - Perform set operations (intersection, union) of image content with structuring element

• Two basic operations
  - Dilation (Matlab: imdilate)
  - Erosion (Matlab:imerode)

• Several important combinations
  - Opening (Matlab: imopen)
  - Closing (Matlab: imclose)
  - Boundary extraction

Matlab:
>> help strel

Image Source: R.C. Gonzales & R.E. Woods
Dilation

• Definition
  - “The dilation of $A$ by $B$ is the set of all displacements $z$, such that $\hat{(B)}_z$ and $A$ overlap by at least one element”.
  - $((\hat{B})_z$ is the mirrored version of $B$, shifted by $z$)

• Effects
  - If current pixel $z$ is foreground, set all pixels under $(B)_z$ to foreground.
    ⇒ Expand connected components
    ⇒ Grow features
    ⇒ Fill holes

Image Source: R.C. Gonzales & R.E. Woods
Erosion

• Definition
  - “The erosion of $A$ by $B$ is the set of all displacements $z$, such that $(B)_z$ is entirely contained in $A$”.

• Effects
  - If not every pixel under $(B)_z$ is foreground, set the current pixel $z$ to background.
    ⇒ Erode connected components
    ⇒ Shrink features
    ⇒ Remove bridges, branches, noise
Effects

Original image

Dilation with circular structuring element

Erosion with circular structuring element

Image Source: http://homepages.inf.ed.ac.uk/rbf/HIPR2/
Effects

Original image

Dilation with circular structuring element

Erosion with circular structuring element

Image Source: http://homepages.inf.ed.ac.uk/rbf/HIPR2/
Opening

- **Definition**
  - Sequence of *Erosion* and *Dilation*
    
    \[ A \circ B = (A \ominus B) \oplus B \]

- **Effect**
  - \( A \circ B \) is defined by the points that are reached if \( B \) is *rolled around inside* \( A \).
  - \( \Rightarrow \) Remove small objects, keep original shape.
Effect of Opening

- Feature selection through size of structuring element

Original image

Thresholded

Opening with small structuring element

Opening with larger structuring element

Image Source: http://homepages.inf.ed.ac.uk/rbf/HIPR2/
Effect of Opening

- Feature selection through *shape* of structuring element

How could we have extracted the lines?

Input Image

Opening with circular structuring element

Image Source: http://homepages.inf.ed.ac.uk/rbf/HIPR2/
Closing

- **Definition**
  - Sequence of **Dilation** and **Erosion**
    \[ A \cdot B = (A \oplus B) \ominus B \]

- **Effect**
  - \( A \cdot B \) is defined by the points that are reached if \( B \) is *rolled around on the outside* of \( A \).
  - \( A \cdot B \) → Fill holes, keep original shape.
Effect of Closing

- Fill holes in thresholded image (e.g. due to specularities)

Original image  |  Thresholded  |  Closing with circular structuring element

Size of structuring element determines which structures are selectively filled.

Image Source: http://homepages.inf.ed.ac.uk/rbf/HIPR2/
Example Application: Opening + Closing

Original image → Opening → Closing

Structuring element:

- Erosion
- Dilatation

Eroded image → Dilated image

Source: R.C. Gonzales & R.E. Woods
Application: Blob Tracking

↓ Absolute differences from frame to frame ↓
Thresholding

↓ ↓

Slide credit: K. Grauman

B. Leibe
Morphological Boundary Extraction

• Definition
  - First erode $A$ by $B$, then subtract the result from the original $A$.
  \[
  \beta(A) = A - (A \ominus B)
  \]

• Effects
  - If a $3 \times 3$ structuring element is used, this results in a boundary that is exactly 1 pixel thick.

Source: R.C. Gonzales & R.E. Woods
Morphology Operators on Grayscale Images

- **Sidenote**
  - Dilation and erosion are typically performed on binary images.
  - If image is grayscale: for dilation take the neighborhood max, for erosion take the min.
Outline of Today’s Lecture

- Convert the image into binary form
  - Thresholding

- Clean up the thresholded image
  - Morphological operators

- Extract individual objects
  - Connected Components Labeling

- Describe the objects
  - Region properties

Image Source: D. Kim et al., Cytometry 35(1), 1999
Connected Components Labeling

- **Goal:** Identify distinct regions

Binary image

Connected components labeling

Sources: Shapiro & Stockman, Chandra
Connected Components Examples

connected components of 1’s from thresholded image

connected components of cluster labels
Connectedness

- Which pixels are considered neighbors?

4-connected

8-connected

Source: Chaitanya Chandra
Sequential Connected Components

- Labeling a pixel only requires to consider its prior and superior neighbors.
- It depends on the type of connectivity used for foreground (4-connectivity here).

What happens in these cases?

Equivalence Table
Sequential Connected Components (2)

- Process the image from left to right, top to bottom:
  1.) If the next pixel to process is 1
     i.) If only one of its neighbors (top or left) is 1, copy its label.
     ii.) If both are 1 and have the same label, copy it.
     iii.) If they have different labels
           – Copy the label from the left.
           – Update the equivalence table.
     iv.) Otherwise, assign a new label.
Sequential Connected Components (2)

- Process the image from left to right, top to bottom:
  1. If the next pixel to process is 1
     i.) If only one of its neighbors (top or left) is 1, copy its label.
     ii.) If both are 1 and have the same label, copy it.
     iii.) If they have different labels
          - Copy the label from the left.
          - Update the equivalence table.
     iv.) Otherwise, assign a new label.

{1}
Sequential Connected Components (2)

- Process the image from left to right, top to bottom:
  1. If the next pixel to process is 1
     - i.) If only one of its neighbors (top or left) is 1, copy its label.
     - ii.) If both are 1 and have the same label, copy it.
     - iii.) If they have different labels
          - Copy the label from the left.
          - Update the equivalence table.
     - iv.) Otherwise, assign a new label.
Sequential Connected Components (2)

- Process the image from left to right, top to bottom:
  1. If the next pixel to process is 1
     i.) If only one of its neighbors (top or left) is 1, copy its label.
     ii.) If both are 1 and have the same label, copy it.
     iii.) If they have different labels
           - Copy the label from the left.
           - Update the equivalence table.
     iv.) Otherwise, assign a new label.

Equivalence table

\[
\begin{bmatrix}
\{1, 2\} & 2 \\
\{2\} & & \\
\end{bmatrix}
\]
Sequential Connected Components (2)

- Process the image from left to right, top to bottom:
  1.) If the next pixel to process is 1
      i.) If only one of its neighbors (top or left) is 1, copy its label.
      ii.) If both are 1 and have the same label, copy it.
      iii.) If they have different labels
            – Copy the label from the left.
            – Update the equivalence table.
      iv.) Otherwise, assign a new label.

- Re-label with the smallest of equivalent labels

Equivalence table

\[
\begin{align*}
\{1\} & \quad 2, \ 7 \\
\{2\} & \quad 3, \ 5, \ 6, \ 8 \\
\{3\} & \\
\{4\} & \\
\{5\} & \\
\{6\} & \\
\{7\} & \\
\{8\} & \\
\end{align*}
\]
Application: Segmentation of a Liver

Application by Jie Zhu, Cornell University
Outline of Today’s Lecture

- Convert the image into binary form
  - Thresholding

- Clean up the thresholded image
  - Morphological operators

- Extract individual objects
  - Connected Components Labeling

- Describe the objects
  - Region properties
Region Properties

- From the previous steps, we can obtain separated objects.

- Some useful features can be extracted once we have connected components, including
  - Area
  - Centroid
  - Extremal points, bounding box
  - Circularity
  - Spatial moments
Area and Centroid

- We denote the set of pixels in a region by $R$
- Assuming square pixels, we obtain

- **Area:**
  \[ A = \sum_{(x, y) \in R} 1 \]

- **Centroid:**
  \[ \bar{x} = \frac{1}{A} \sum_{(x, y) \in R} x \]
  \[ \bar{y} = \frac{1}{A} \sum_{(x, y) \in R} y \]

Source: Shapiro & Stockman
**Circularity**

- Measure the deviation from a perfect circle

  - **Circularity:**
    \[ C = \frac{\mu_R}{\sigma_R} \]
    where \( \mu_R \) and \( \sigma_R^2 \) are the mean and variance of the distance from the centroid of the shape to the boundary pixels \((x_k, y_k)\).

  - **Mean radial distance:**
    \[ \mu_R = \frac{1}{K} \sum_{k=0}^{K-1} \left\| (x_k, y_k) - (\bar{x}, \bar{y}) \right\| \]

  - **Variance of radial distance:**
    \[ \sigma_R^2 = \frac{1}{K} \sum_{k=0}^{K-1} \left[ \left\| (x_k, y_k) - (\bar{x}, \bar{y}) \right\| - \mu_R \right]^2 \]

Source: Shapiro & Stockman
Invariant Descriptors

- Often, we want features independent of location, orientation, scale.

\[
\begin{bmatrix}
    a_1, a_2, a_3, \ldots \\
    b_1, b_2, b_3, \ldots
\end{bmatrix}
\]

Feature space distance
Central Moments

- $S$ is a subset of pixels (region).
- Central $(j,k)^{th}$ moment defined as:
  \[
  \mu_{jk} = \sum_{(x,y) \in S} (x - \bar{x})^j (y - \bar{y})^k
  \]
- Invariant to translation of $S$.

- Interpretation:
  - $0^{th}$ central moment: area
  - $2^{nd}$ central moment: variance
  - $3^{rd}$ central moment: skewness
  - $4^{th}$ central moment: kurtosis

Slide credit: Kristen Grauman
Moment Invariants ("Hu Moments")

- Normalized central moments

\[ \eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^\gamma}, \quad \gamma = \frac{p+q}{2} + 1 \]

- From those, a set of invariant moments can be defined for object description.

\[ \phi_1 = \eta_{20} + \eta_{02} \]
\[ \phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \]
\[ \phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \]
\[ \phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \]

- Robust to translation, rotation & scaling, but don’t expect wonders (still summary statistics).
Moment Invariants

\[
\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
+ (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]
\]

\[
\phi_6 = (\eta_{20} - \eta_{02})\left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \\
+ 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})
\]

\[
\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
+ (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]
\]

Often better to use \(\log_{10}(\phi_i)\) instead of \(\phi_i\) directly...
Axis of Least Second Moment

- Invariance to orientation?
  - Need a common alignment

- Compute Eigenvectors of $2^{nd}$ moment matrix ($\text{Matlab: eig}(A)$)

\[
\begin{bmatrix}
\mu_{20} & \mu_{11} \\
\mu_{11} & \mu_{02}
\end{bmatrix} = VDV^T =
\begin{bmatrix}
v_{11} & v_{12} \\
v_{22} & v_{22}
\end{bmatrix}
\begin{bmatrix}
\lambda_1 & 0 \\
0 & \lambda_2
\end{bmatrix}
\begin{bmatrix}
v_{11} \\
v_{21}
\end{bmatrix}
\begin{bmatrix}
v_{12} \\
v_{22}
\end{bmatrix}^T
\]
Summary: Binary Image Processing

- **Pros**
  - Fast to compute, easy to store
  - Simple processing techniques
  - Can be very useful for constrained scenarios

- **Cons**
  - Hard to get “clean” silhouettes
  - Noise is common in realistic scenarios
  - Can be too coarse a representation
  - Cannot deal with 3D changes
References and Further Reading

- More on morphological operators can be found in

- Online tutorial and Java demos available on
Questions ?
Demo “Haribo Classification”
You Can Do It At Home...

Accessing a webcam in Matlab:

```matlab
function out = webcam
% uses "Image Acquisition Toolbox",
adaptorName = 'winvideo';
vidFormat = 'I420_320x240';
vidObj1 = videoinput(adaptorName, 1, vidFormat);
set(vidObj1, 'ReturnedColorSpace', 'rgb');
set(vidObj1, 'FramesPerTrigger', 1);
out = vidObj1;

cam = webcam();
img = get snapshot(cam);
```
Questions ?